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Climate Change Impacts on Western Reservoir Operations: A Case Study of Bull Run Watershed, Portland, Oregon

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Abstract

Climate change has the potential to alter the quantity and timing of runoff, which may pose significant challenges for the reservoir management. This study evaluates the projected climate impact on the reservoir system of Portland, Oregon. Using sixteen climate models spanning four emission scenarios, the performance reservoir operating policies and their sensitivity to the choice of GCMs and time periods are assessed. Use of historical rule curves for reservoir operations results reduces forecast reliability for future periods. This general trend for decreasing forecast reliability for future periods is not sensitive to the choice of GCM. Regardless of the selected reservoir policy model, the results suggest a similar range of reliability (62%- 74%), implying that there is no optimal model for the operation of the reservoir.

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1. Introduction

The well-known associations between recent increases in greenhouse gases, increased global average temperature, and hydrologic fluxes raise important concerns for reservoir management (Heino et al. 2009, IPCC, 2014). In particular, seasonal changes in the timing of precipitation, snowmelt and streamflow result in an earlier spring freshet (Cayan et al. 2001, Dettinger et al. 2004; Stewart et al. 2004; Hamlet and Lettenmaier, 2007). This shift in snowmelt timing can also decrease overall water availability because earlier runoff may not be captured by reservoirs (Dettinger and Cayan, 1995). It is well recognized by water resources planners that climate change scenarios should be considered in planning future reservoir operation rules (Lee et al. 2009).

Changes in temperature and precipitation caused by climate change have been connected to overall declines in the runoff in the western United States. The likely implications of climate change on high elevation streams in the western US show a reduction in annual discharge during spring (Aguado et al. 1992, Dettinger and Cayan 1995). This change has also been identified in Northwest in recent decades. Assessment of trends of the annual streamflow in Pacific Northwest streams found a declining trend in the 25th percentile annual streamflow in the majority of the gaging stations, with half of them declining from 29% to 47% from 1948 to 2009 (Luce and Holden, 2009). The investigation of the long- term water availability under future climate change conditions in North Platte watershed in Wyoming projected decreased water availability during winter months, and also drying in the summer months (Acharya et al. 2011).

Both declines in total water availability and earlier runoff are common across the western US and are related to temperature and precipitation patterns for snow dominated areas from Alaska to Mexico (McCabe and Clark 2005; Fritze et al. 2011). Stewart et al. (2005) used several metrics to demonstrate a temperature-associated shift to earlier snowmelt and peak streamflow by one to 4 weeks, relative to longer term records. Conversely, delayed streamflow timing is common in coastal rain dominated areas from Washington to California (Fritze et al. 2011).

Future climate change will likely continue to affect streamflow patterns, which may pose significant challenges for reservoir management (Nawaz and Adeloye, 2006; Lopez et al. 2009, Stocker et al. 2013). Such modified reservoir release policies have been developed as adaptation strategies to hydrologic shifts caused by climate change (Eum and Simonovic, 2010 in Nakdong River basin in Korea; Hamlet, 2011 in Pacific Northwest Region of North America; Zhou and Guo, 2013 in china's Danjiangkou reservoir; Stagge et al. 2017 in Washington, DC). In the northwest USA, an analysis of reservoir rule curves for the Colombia river basin showed that a warmer climate reduces the effectiveness of reservoir operations (Lee et al. 2009). Similarly, simulations of reservoir operations for three future periods in Colorado River Basin projected a decrease in the probability of meeting demand from 92% in a historical climate simulation to 59% to 75% for future simulations. However, another study found that using reservoir balance models developed for a reservoir in Italy, climate change scenarios did not significantly affect the reservoir resilience (Mereu et al. 2016). Differences in climate change vulnerability between systems highlight spatial variability in climate change impacts as well as water management infrastructure.

In addition to spatial differences there is also great variability among, and uncertainty within future climate projections. Analysis of future water availability generally relies on outputs from global climate models. Climate projections derived from Coupled Atmospheric-Ocean General Circulation Models (AOGCM) are commonly used to assess the future impacts of climate change on water resources at both global and regional scales (Wilby and Harris, 2006). However, the great variability among GCMs and the uncertainty surrounding their projections pose a significant challenge to water managers who seek to understand future impacts of climate change on long- term water supply for local systems (Wang et al. 2016). Variability among models derives from several sources including the differences in GCMs structures, the greenhouse gas emission scenario applied, and the approach used to downscale the coarsely gridded GCMs data (Wilby and Harris, 2006; Kay et al. 2009). Previous analyses have evaluated uncertainties in temperature and precipitation outputs (Rowell, 2006; Deque et al. 2007; Fowler and Ekstrom, 2009) as well as the uncertainties impact of this variability on predicted runoff (Stainforth et al. 2005; Horton et al. 2006; Prudhomme and Davies; 2009, Chen et al. 2011; Teutschbein et al. 2011). Uncertainty and bias in the prediction of hydrological variables directly translate to model skill for reservoir management, which are highly dependent on an accurate prediction of inflow. While regional trends in the timing and magnitude of streamflow have been explored in the western U.S., less has been done to evaluate adverse local consequences of climate change on individual reservoir systems. Here we evaluate projected climate impacts on the reservoir system that serves Portland, Oregon. We combined downscaled climatic projections with an optimization model to develop and evaluate the performance of reservoir rule curves. Sixteen climate models spanning four emission scenarios are used to assess potential future reservoir reliability to a range of streamflow projections in three different periods. Using this suite of simulations, we evaluate:

1. The response of temperature, precipitation, and streamflow to climatic change in the study area

2. The performance of historical reservoir operating policies for climate

3. The sensitivity of reservoir policies and performance to various GCMs and time periods

2. Methods

This study assesses and quantifies the impact of simulated temperature, precipitation, and streamflow changes on the operation of a reservoir system, based on outputs from downscaled GCMs combined with a hydrologic model. Figure 1 shows the overall approach. First, historical simulations and future projections of climatic and hydrologic variables are obtained from US Bureau of Reclamation (BOR) database and evaluated to see the response of meteorological and hydrologic variables to different scenarios (Section 2.1). These hydrologic simulations are then used as inputs to a reservoir optimization model, which determines the optimal reservoir operation rule curves given a time series of reservoir inflows (Section 2.2). The extracted rule curves are first used to simulate reservoir outflows and determine the reliability of water supply for the historical data. The rule curves were then used with simulated future streamflow projections from multiple GCMs (Section 2.3) as well as fitting and simulation periods (Section 2.4) to evaluate the sensitivity of reservoir operations to various model configurations.

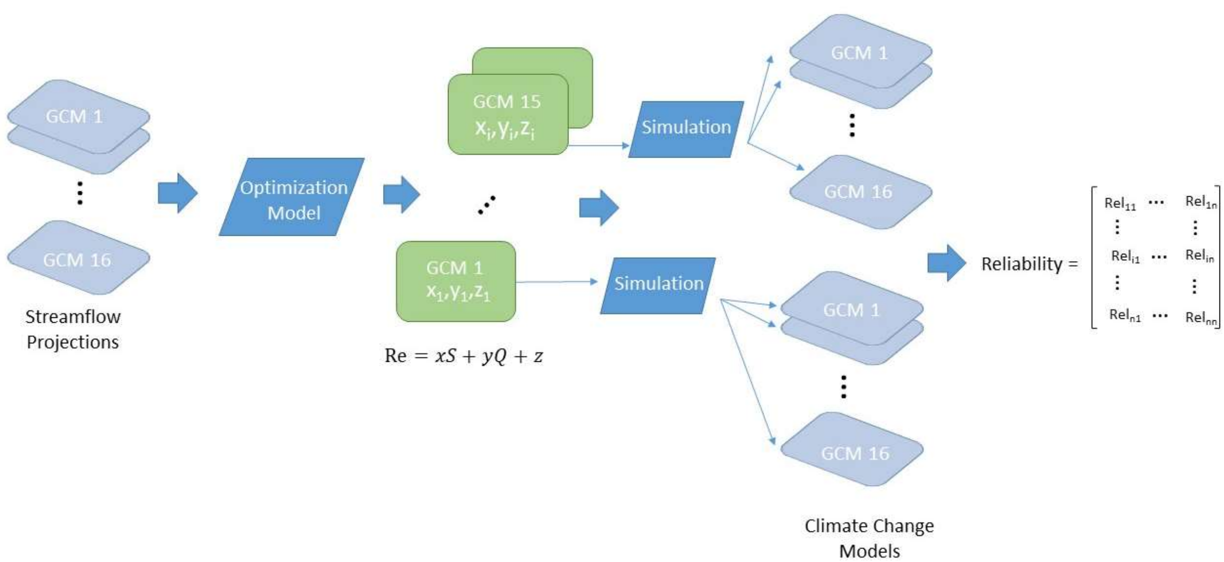

Fig 1. Schematic overview of optimization- simulation of climate change datasets. Streamflow projections are presented in light blue rectangles, individual optimization and simulation processes are shown in blue parallelogram, and green rectangles illustrate rule curved fit over different GCMs

2.1 Study domain and hydrologic inputs

We evaluate reservoir management practices in the Bull Run Watershed, which is located approximately 48 km east of Portland (Figure 2). The 264 km^2 Bull Run River drainage basin is contained within the 386 km^2 Bull Run Watershed Management area. The watershed mean annual precipitation is 330 cm of rain and snow (Chang et al. 2014). The mean annual streamflow is approximately16 m^3/s. The river drains into Bull Run Reservoirs 1 and 2. Both reservoirs were constructed for water storage and can hold a combined total of 64 MCM.

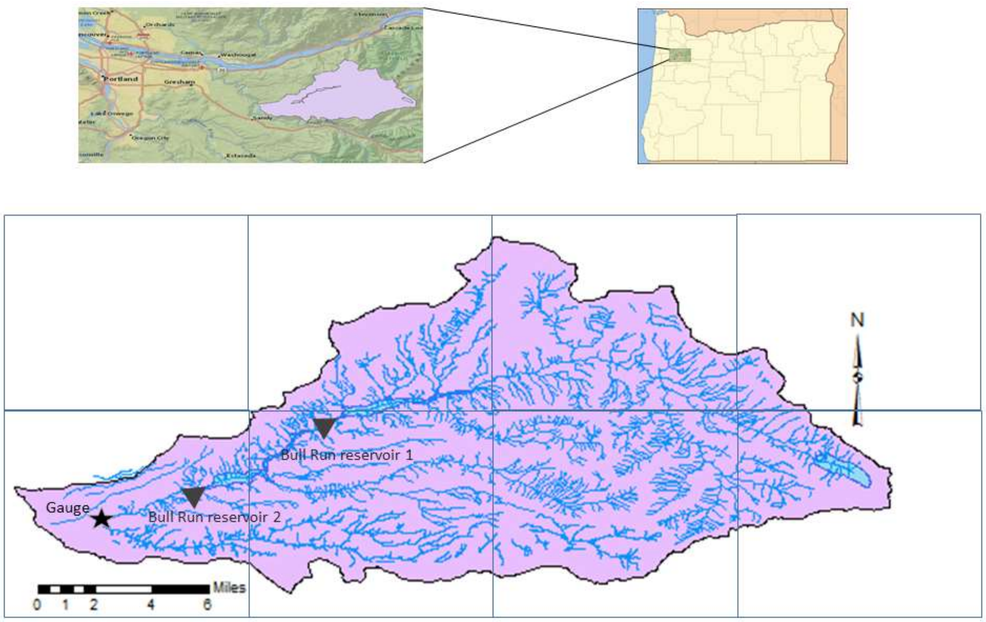

Fig 2. Map of the Bull Run watershed showing the locations of the two storage reservoirs (black triangles) and the river system (blue lines) as well as the gauging station (black star)

Bull Run Reservoir 1 is upstream and has a storage capacity of 38 MCM. It was built in 1929 to supplement the water supply for the city of Portland. It lies near the center of the Bull Run Reserve, a restricted area of 554 km^2 that provides a reliable supply of clean water for nearly one-third of all Oregon population. Downstream of Bull Run Reservoir 1, Bull Run Reservoir 2 was constructed in 1961. It lies at the western end of the Bull Run Reserve and holds an interannual storage of 26 MCM of water for use of the City of Portland and adjacent areas. For the purposes of this analysis, we treat both reservoirs as a single reservoir with a total storage of 64 MCM.

This study analyzes historical and future hydrologic reliability of the combined reservoir system using downscaled GCM projections. Monthly gridded values of GCM simulated temperature, precipitation, and streamflow from 1950-2099 were obtained through the U.S. BOR Climate projection database (Maurer et al. 2007; Brekke et al. 2013) which includes downscaled hydrologic outputs from the Coupled Model Intercomparison Project Phase 5 (CMIP5). All outputs are provided at 1/8-degree spatial resolution (approximately 144 square km) which results in 6 grid cells to cover the study domain (Figure 2). All simulations follow historical observed climate from 1950-1999 (henceforth referred to as the 'Historical Period') and rely on emissions scenarios for the period from 2000-2099 (henceforth referred to as the 'Future Period').

Precipitation and temperature were statistically downscaled to $1/8^{th}$ degree resolution from GCM outputs by Reclamation using the Bias Correction and Statistical Downscaling (BCSD) method (Wood et al. 2002). Future projections are based on greenhouse gas emissions scenarios, referred to as Representative Concentration Pathways (RCPs) as described in the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC) (IPCC, 2014). The four pathways described by IPCC are RCP2.6, RCP4.5, RCP6, and RCP8.5 where the numeric values represent the radiative forcing (Wm^2) in 2100 relative to preindustrial conditions. Each scenario is simulated using multiple GCMs: 32 models for RCP2.6, 16 models for RCP4.5, 26 models for RCP6.0, and 31 models for RCP8.5.

GCMs do not simulate terrestrial hydrology; therefore, the downscaled precipitation and temperature outputs must be run through hydrologic models to generate projections of hydrologic variables such as streamflow. Reclamation disaggregated the BCSD downscaled climate variables to a daily time step and applied these daily projections as inputs to the Variable Infiltration Capacity (VIC) hydrologic model (Liang et al. 1994) to generate gridded streamflow projections from 1950-2099 across US (Maurer et al. 2002). The daily simulations (at the VIC grid-scale) are then resampled to the monthly values. Here, to have a more manageable subset of projections for reservoir optimization, we use an ensemble of 16 streamflow projections obtained from the Reclamation database for our study area as inputs for reservoir analysis. As shown in Table 1, we have selected four models for each RCP.

Table 1: Climate simulates selected for analysis grouped by RCP

Emission Scenario	RCP2.6	RCP4.5	RCP6.0	RCP8.5
GCMs	bcc-csm1-1	fio-esm	giss-e2-r	miroc-esm
	ccsm4	gfdl-cm3	hadgem2-ao	miroc-esm-chem
	cesm1-cam5	gfdl-esm2g	hadgem2-es	miroc5
	csiro-mk3-6-0	gfdl-esm2m	ipsl-cm5a-mr	noresm1-m

2.2. Reservoir simulation

A reservoir system can be simulated using the continuity equation to evaluate reservoir storage volume in each period of operation based on reservoir inflow, water releases, and losses as follows:

$$S_{t+1} = S_t + Q_t - Re_t - Sp_t - Loss_t \quad (1)$$

Where t is the number of operational period; S_t and S_{t+1} are the reservoir storage volume at the beginning of time period t and t+1, respectively (here we use a monthly time step to match the hydrologic inputs); Q_t is the river inflow volume to reservoir during period t; Re_t is volume of released water from the reservoir during period t; Sp_t is volume of spilled water from the reservoir during period t; and $Loss_t$ is volume of evaporation losses from the reservoir during period t.

Reservoir inflows are assumed to be the streamflow entering the reservoir (in this case the VIC simulated streamflows) and outflows are determined by operating rules described in Section2.3. If storage exceeds the total reservoir volume, it is assumed that this water is ‘spilled’. This constraint is applied as shown in Equation (2).

$$Sp_t = \begin{cases} S_t + Q_t - Re_t - S_{\max} & if \quad S_t + Q_t - Re_t > S_{\max} \\ 0 & if \quad S_t + Q_t - Re_t \le S_{\max} \end{cases} \tag{2}$$

Additional relevant constraints include:

$$S_{\min} \le S_t \le S_{\max} \tag{3}$$

$$Re_{\min} \le Re_t \le Re_{\max} \tag{4}$$

Where S_{min} and S_{max} are the minimum and maximum storage of reservoir, respectively; and Re_{min} and Re_{max} are the minimum and maximum allowable capacities of the reservoir release, respectively.

2.3. Reservoir optimization

The reservoir simulation model described above simulates reservoir storage given reservoir inflow and releases which are assumed to follow some pre-defined rule curves. It does not determine the best (optimal) operating policies of the system. To determine an optimal/near-optimal solution, an optimization model should be coupled with simulation. Here we focus on optimizing a reservoir release policy (i.e. rule curve) to minimize unmet demand given inflows.

A rule curve is a mathematical equation which specifies the timing and volume of releases from the reservoir (Re_t) given the current state of the system (e.g. storage amount and reservoir inflows). Many types of operational rule curves have been applied to different systems (e.g. Louks, 1970, Eisel; 1972, Loucks and Dorfman; 1975; Karamouz and Houcks, 1982). In this study, we apply the Linear Decision Rules (LDR) introduced by Karamouz and Houcks (1982) which are a commonly applied approach. The LDR used here is given in Equation 5.

$$Re_t = xS_t + yQ_t + z \tag{5}$$

Where x, y, and z are the function coefficients of the rule curve that must be derived. The rule curve shown above can be used in real time operation (i.e. determining the releases at any point in time given the current state of the system). However, here we apply the rule curve to long-term simulations in order to evaluate system performance as a function of the rule curve parameters.

Optimal rule curve parameters (x, y, z) can be determined using long-term time series of inflow and water demand combined with an objective function. In this study, the objective function is to minimize the total unmet demand (i.e. the difference between the water released from the reservoir and the downstream demand) as given in Equation 6:

$$UD = \sum_{t=1}^{N} \left(\frac{D_t - Re_t}{D_t}\right)^2 \tag{6}$$

Where UD is the objective function, which represents the total unmet demand over the simulation period. Here, N is the number of operational periods and D_t is the downstream demand of reservoir at period t. Demand data are obtained from water management and conservation plan report for city of Portland (Portland Water Bureau, July 2010). According to the report, the total annual demand for city of Portland equals 176 MCM with peak demand in July. The optimal reservoir operation policy is determined by adjusting the three coefficients in the rule curve (Equation 5) in order to minimize UD. Here we employ Genetic Algorithms (GA)

(Chen et al., 2017) to optimize the constant variables of rule curve equation, which extracts optimal operation policies by minimizing water shortages. Optimization is carried out using MATLAB inbuilt GA tool box which provides a tool for the inputs of the reservoir and the constraints.

2.4 Test cases

We evaluate reservoir operations across a suite of time periods and GCM simulations in order to compare the performance of operating policies derived from different climate models and time periods. Figure 3 outlines the general approach. First, a rule curve is derived for a single GCM model over a given time period, referred to as the *fitting period*, by optimizing the rule curve parameters given the hydrologic inputs of the fitting period. Next, the rule curve is used to simulate reservoir operations over a different time period or for a different GCM using the hydrologic inputs of that time period and model. This is referred to as the *simulation period*. Finally, outputs from the simulation are analyzed to evaluate reservoir performance. The reservoir simulation provides reservoir releases at every time step which are used to calculate unmet demand and overall reliability. Reliability is defined as the probability that the water supply system satisfies demand and is calculated using Equation 7 (McMahon et al. 2006) as follows:

$$Reliability = \frac{N_S\ (Re \geq D\ \ )}{N} \tag{7}$$

Here, N_s is the number of periods that the demand is satisfied and N is the total number of periods in the simulation.

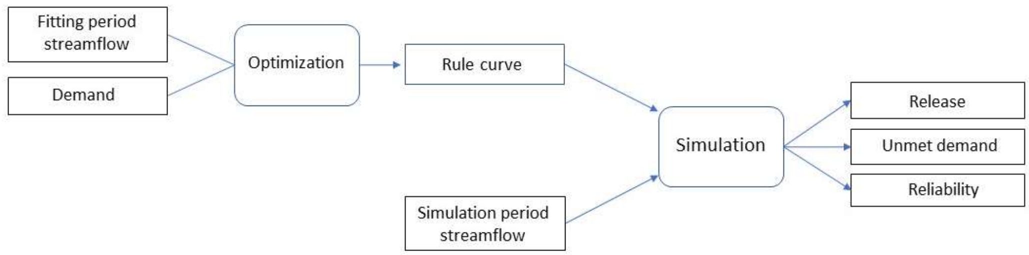

Fig 3. Schematic of optimization- simulation of reservoir system

The approach outlined in Figure 3 is repeated to evaluate reservoir operations for an ensemble of streamflow projections covering the 16 GCMs selected for the analysis. Rule curves are developed from monthly data for three sets of 30-year future fitting periods that span the 2000–2090 future simulation period; 2000-2030, 2031-2060, 2061- 2090. The historical period is also divided into two 30-year fitting periods (1950-1980 and 1970-1999). This results in 48 future rule curves (16 GCMs times 3 fitting periods) and 2 historical rule curves. Note that the GCMs have the same simulated streamflow for the historical time period so historical rule curves only need to be fit once.

Using these rule curves, we complete a suite of simulations. First, the historical rule curves are used to simulate the streamflow time series of the 16 models in the three future periods. These simulations are used to evaluate how reservoir operating policies based on historical local hydrology are likely to perform in the future. Next, comparisons between simulations are used to quantify the sensitivity of projected changes to the choice of historical period used for fitting period, and also the selected GCM. We then evaluate reservoir performance using future fitting periods to determine if reliability can be improved by incorporating projected changes into the rule curve. Finally, we evaluate the sensitivity of this performance by comparing the performance of each model simulating itself and simulating the other 15 GCMs. Simulation of itself means the fitting inputs and simulation inputs come from different time periods of the same GCM, called on-self, while simulation of other GCMs refers to the case when a rule curve is fit to one GCM but used to simulate reservoir performance using simulated reservoir inflows from other GCMs called on- other.

3. Results

3.1 Historical Hydrologic simulations

Before simulating reservoir operations, we evaluate the downscaled GCM and VIC simulations from Reclamation database (Maurer et al. 2007). First, we compare historical simulations to observed hydrology in the basin. Precipitation, maximum temperature, and streamflow simulations generated from downscaled climate simulations and VIC were compared with the 1950 to1999 observation data. Note that, the simulated variables over the historical period are the same for all simulations whereas the GCM simulations diverge over the future period, which starts in 2000. Simulated precipitation and temperature are compared to observations from the National Oceanic and Atmospheric Administration-National Weather Service (NOAA-NWS). The simulated values of the grid cell where the gauging station is located is used to compare with the observation data. Simulated streamflow, which is the outflow from the domain, is compared to observations from USGS Gage No. 14140000. Figure 4 illustrates monthly mean precipitation, temperature, and streamflow in the Bull Run watershed for the historical period.

Bull Run watershed is a snow-dominated basin. As shown in Figure 4c, streamflow begins to increase in February, in response to the corresponding warming and associated snowmelt. There is generally a good agreement in seasonal timing between observed and simulated streamflow. However, the simulated streamflow is much greater than observed from February to July. This is partially related to greater precipitation in the simulations (Figure 4b), but is likely also due to storage effects of the reservoirs located upstream of the stream gauge. There is also temperature bias in the simulations; the observed temperature is about 1 degree higher than the simulated temperature from January to July (Figure 4a). This bias is likely due to elevation differences between the temperature observations (which occur at a point) and the roughly 12 km^2 model grid cell.

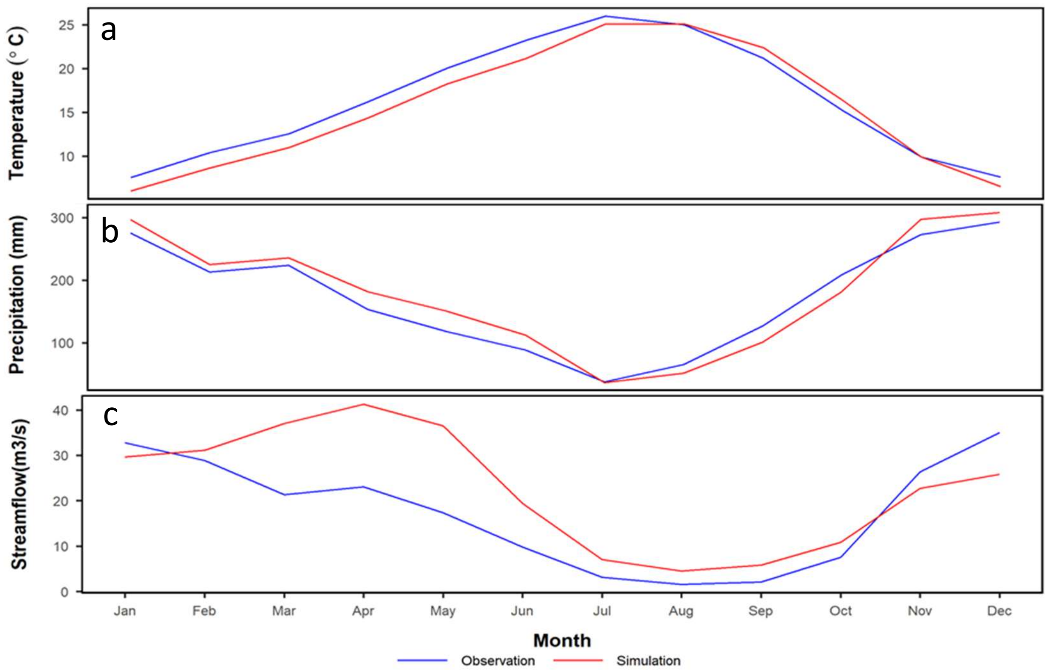

Fig. 4 Monthly observed (blue) and simulated (red) mean of temperature (a), precipitation (b), and streamflow (c) in Bull Run watershed, 1950-1999.

Figure 5 shows the strong correspondence between annual precipitation, temperature, and streamflow in Bull Run watershed for the study period. According to the figure, streamflow simulation is very close to measured streamflow for the first nine years after 1950, but diverges substantially by 1960. Thereafter, the extent of difference appears to be a function of streamflow magnitude. There were periods of low streamflow in the early 1950s, late 1980s, and early 1990s, and wet periods in the early 1970s and mid-1990s. Streamflow had a noticeable rise in the mid- 1990s and then showed strong inter-annual variability in the late-1990s. High flow periods correspond to wet precipitation years (Figure 5b). For example, in 1996 there was a sharp increase in precipitation which resulted in a dramatic increase in streamflow. There is also strong inter-annual variability in temperature. Over the historical period, annual temperature varies between 13 and 17.5°C. Similar to the seasonal comparison, Figure 5 shows a consistent wet bias in precipitation and a cool bias in temperature, which combined result in a high bias in streamflow. Comparing the temperature results between simulation and observations illustrates a difference from 1°C to 2.5°C. Overall, the simulation of the temperature is lower than the observation values for the historical period. Again, this bias is likely caused by elevation differences between grid elevations and observation gauge.

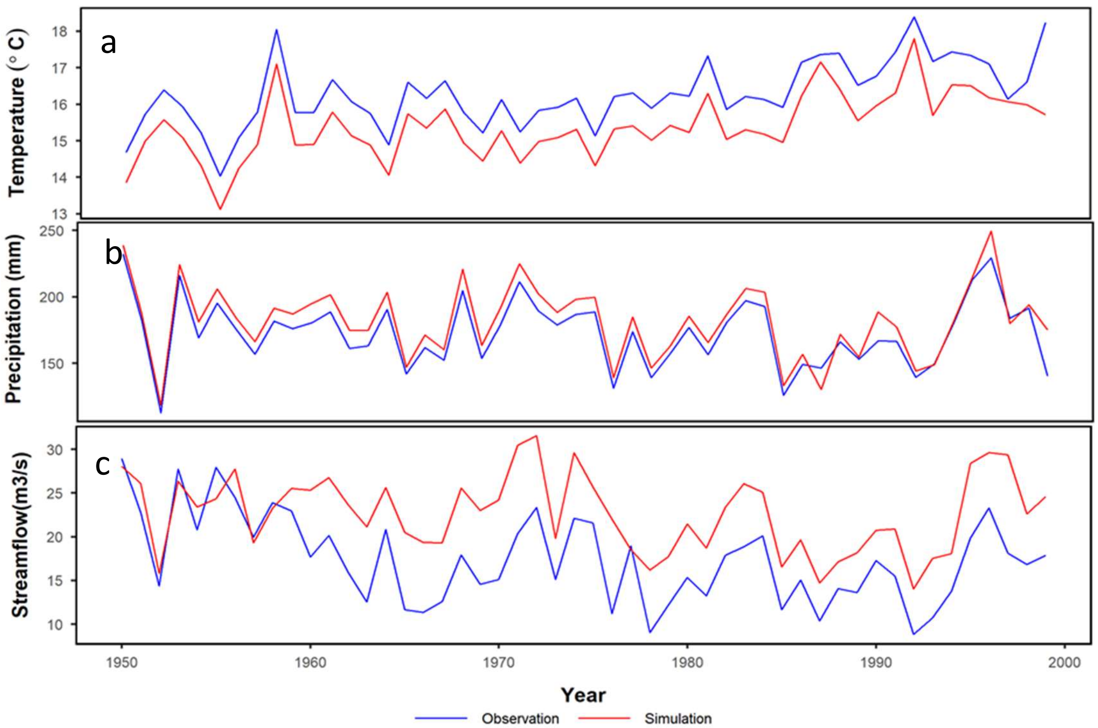

Fig. 5 Annual observed (blue) and simulated (red) mean of temperature (a), precipitation (b), and streamflow (c) in Bull Run watershed.

3.2 Future Hydrologic Simulations

This section summarizes the climate and hydrologic simulations from 31 GCMs that span four emission scenarios to see the response of temperature, precipitation, and streamflow to climatic change in Bull Run watershed. Future projections were obtained from Reclamation database (Maurer et al. 2007). In the subsequent sections, we use these simulated values to (1) derive optimized reservoir rule curves and (2) evaluate the impact of simulated hydrologic changes on reservoir reliability.

Figure 6a illustrates the projected changes in precipitation under the four RCPs for the years 2000- 2099. While there is a great variability among simulations, there are no apparent systematic differences and no indication of change in annual precipitation from 2000 to 2099. The annual precipitation obtained by the ensemble of GCMs ranges from 4000 mm to 14000 mm with mean value equal to 7500 mm.

Temperature projections from CMIP5 models all show a similar gradual increase in temperature over the Bull Run watershed for all the RCP scenarios from 2000 to 2050 (Figure 6b). At longer time scales, the RCP scenario temperatures start to diverge and the temperature is significantly higher by 2099 for RCP 8.5 as compared to RCP 2.6. Some individual ensemble members show warming exceeding 2°C after 2000 and the maximum increase for RCP 8.5 could approach 10°C by 2099.

Annual streamflow projections of VIC model, and the same downscaled GCM outputs of precipitation and temperature show temporal variability in all scenarios but no clear trend (Figure 6c). The mean ensemble values for annual streamflow from the four scenarios are identical for 2000 to 2099. The ensemble of climate models suggests that streamflow ranges from 100 to 600 m^3/s with ensemble mean equal to 280 over this period.

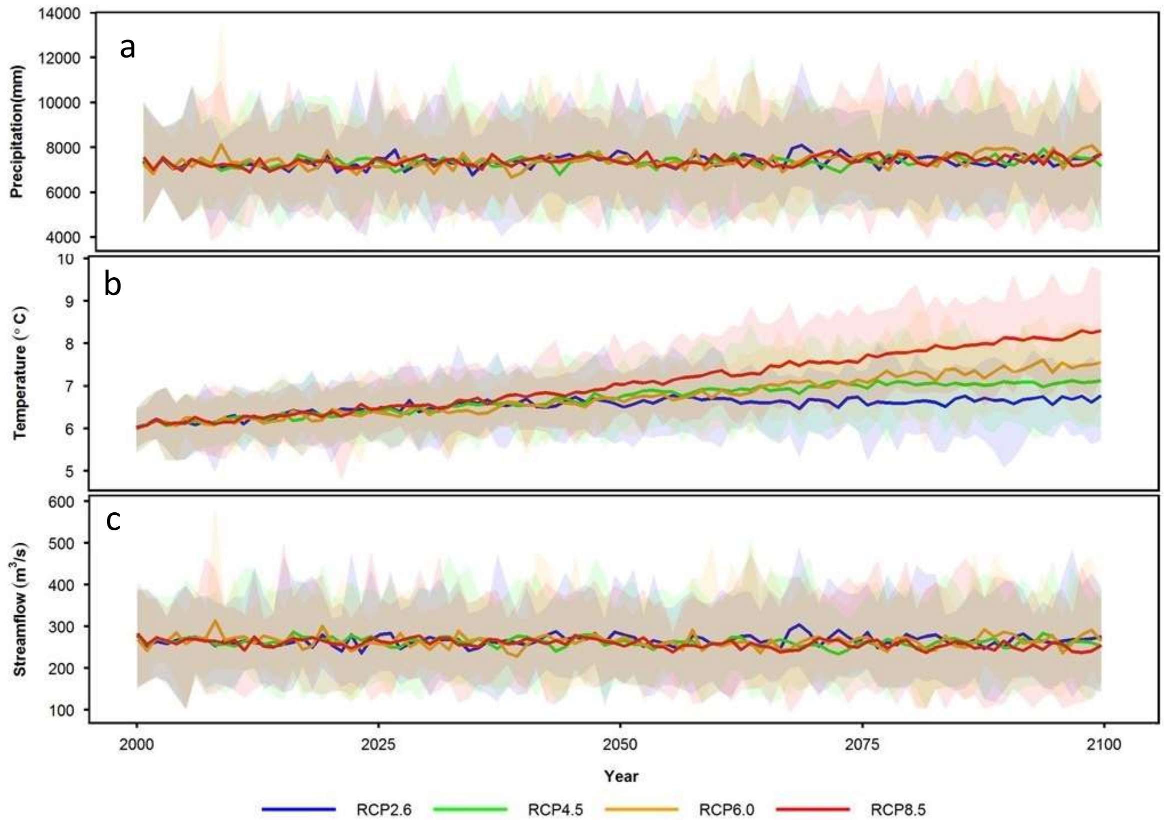

Fig 6. CMIP5 ensemble mean, maximum, and minimum of annual precipitation (a), annual average temperature (b), and annual streamflow (c) for the period of 2000–2099. Colors represent different RCPs, shadings denote the projected range (min and max) of GCMs, and lines show average of annual mean across GCMs. Note: the gray color is due to the overlap of four adjacent colors

Figure 7 presents the projected and historical monthly mean precipitation, maximum temperature, and streamflow and also anomalies showing the difference between future (2000 to 2099) and historical (1950 – 1999) monthly mean conditions. The mean monthly rainfall from the four scenarios are very similar and the variability is similar to the historical precipitation (Figure 7a). The monthly mean values show that the wet season will likely become slightly wetter, and the dry season will become drier. Moreover, some models show that precipitation may be less than the historical observations by nearly 200 mm. The results also show that the predicted changes in monthly precipitation are greater for wet seasons than dry seasons which is consistent with other regional analysis by Peirce et al. (2013) and Polade et al. (2017).

The temporal patterns of ensemble mean, maximum, and minimum of mean monthly maximum temperature under all scenarios are similar, only the magnitude is different (Figure 7c). Broadly, the expected monthly temperature under different climate change scenarios and conditions indicate that the overall climate will become much warmer as time passes with an increase ranging from 0.5°C to 1°C in December and from 1°C to 1.8°C in July. The maximum difference may reach 2.5°C under RCP8.5 during February and July. This increase in temperature is consistent with other regional studies (e.g. Harding et al. 2012).

As shown in Figure 7e, the discharge for all RCPs is projected to be greater in winter and fall (Jan-Mar and Oct- Dec) and less in the spring and summer (April – August), consistent with current discharge patterns. Increases in air temperatures are expected to have significant impacts on amount and timing of annual runoff from watersheds that receive substantial precipitation in the form of snow (Das et al. 2009). The mean timing of peak discharge in Bull Run watershed is advanced under all four RCPs (figure 7e). Figure 7f shows that the modeled fraction of runoff from April through July decreases through time for all scenarios, as air temperature increases. This indicates that a greater fraction of snowmelt occurs before April 1 as a result of increased air temperatures. These results are consistent with other regional analysis by Dickerson-Lange and Mitchell (2014) that showed an increase in winter flows, a decrease in summer flows, and a shift in timing of the streamflow peak.

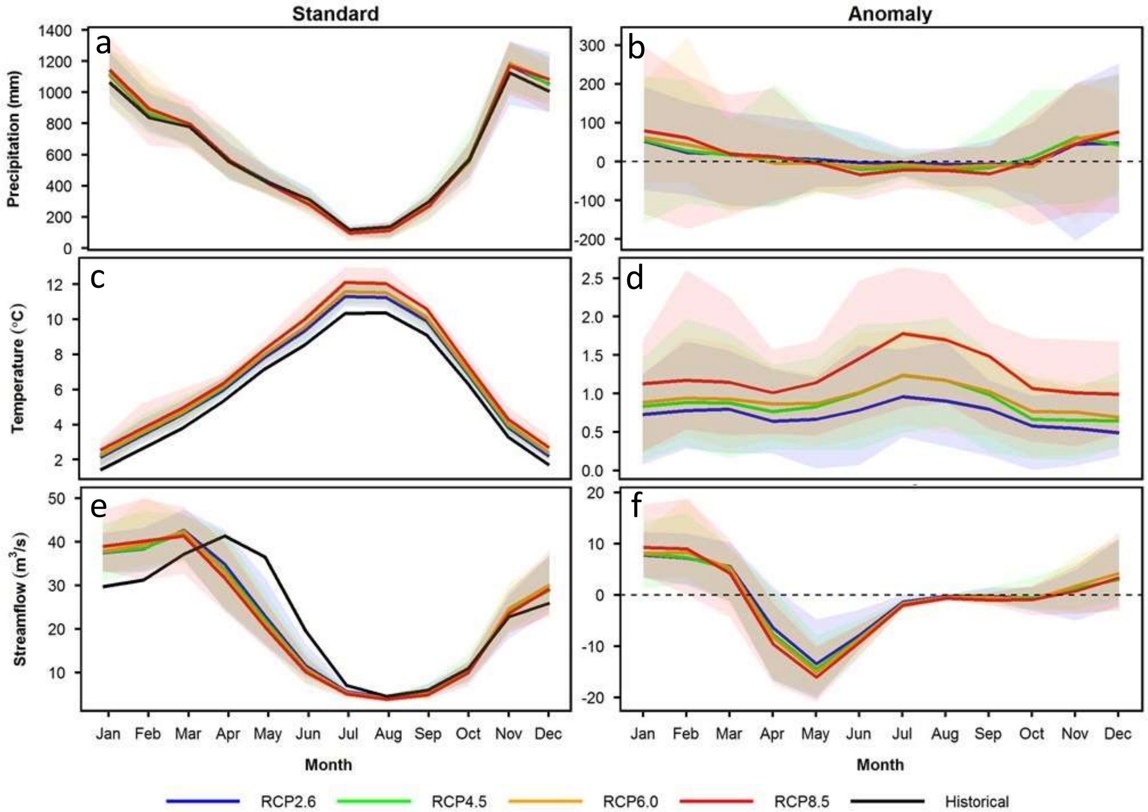

Fig 7. CMIP5 ensemble mean, maximum, and minimum of monthly (left) and monthly anomalies relative to 2000–2099 (right) of precipitation, maximum temperature, and streamflow for the period of 1950–2099. Colors represent different RCPs, shadings denote the projected range of GCMs, and lines show average of monthly mean across GCMs

3.3 Reservoir Performance

In order to evaluate the performance of historical reservoir policy in future periods, we first apply rule curves fit to historical conditions (i.e. 1950-1999) to projected streamflow time series of representing 16 GCMs for the period 2000- 2090. Figure 8 shows the simulated result of reservoir releases for historical and future periods. Simulation results for the future period illustrate the large variability across GCM projections for future periods. While there is no consistent trend between GCM projections, there is an increased likelihood of releases lower than the historical minimum of 158 MCM, in the future. Taking into account all of the simulations, the probability of releases falling below the threshold of 167 MCM (95% of annual demand) is greater in the future period.

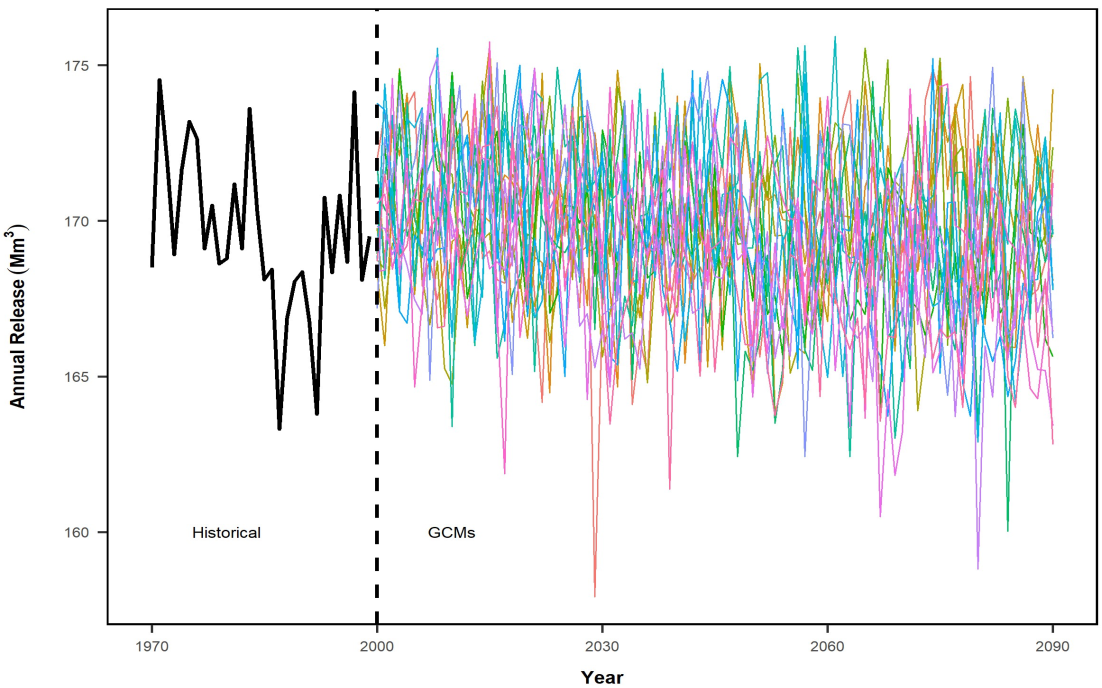

Fig 8. Time series of annual release of reservoir simulated using historical (1970- 1999) rule curve. Colors represent releases simulated using streamflow projected by different GCMs

Comparison of the simulated reservoir reliability across all 16 models for three future time periods to the reliability over the historical simulation period (solid line) shows that the projected long-term reliability is generally less than the historical period (Figure 9). The near-term (2000 to 2030) reliability is slightly greater than the historical reliability; however, this decreases moving further into the future. Similar to the reservoir release time series shown in Figure 8, substantial variability remains among scenarios, and some GCMs maintain high reliability even in the 2060– 2090 period.

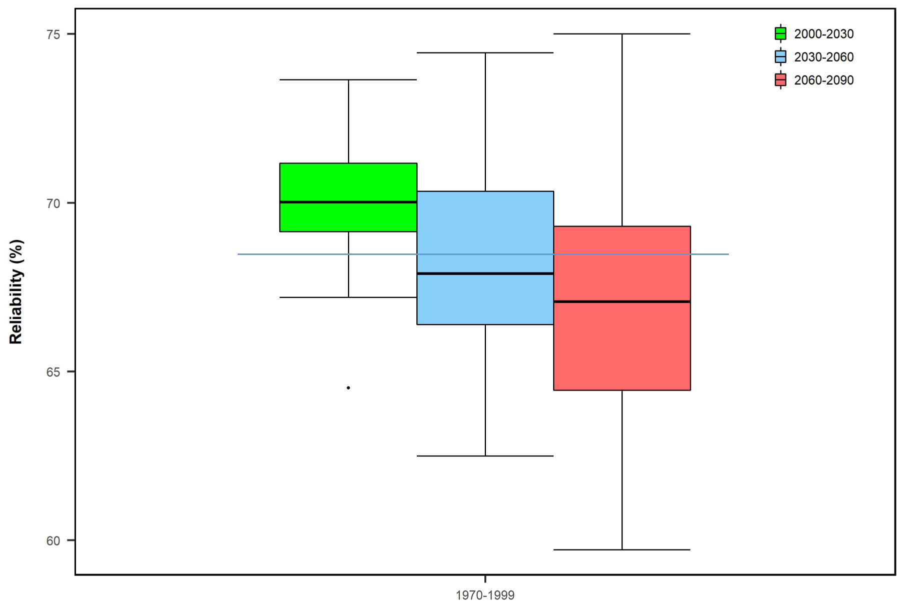

Fig 9. Future simulated reservoir reliability using rule curve fit to simulated historical stream flow from 1970 – 1999. Solid line represents the simulated reliability over the historical simulation period

The trends in reliability shown in Figure 9 are consistent with the shifting streamflow timing trends shown in Figure 7. To illustrate this further, the cumulative probability of the seasonal discharge under all RCPs for the period of 2000 to 2090 indicates consistently drier future conditions from April through June, compared to the historical period. In contrast, the January to March period indicates wetter conditions. Both high flows and low flows are projected to increase during winter season under all four scenarios. However, for the period April to June, a general decrease in flow is projected, potentially aggravating summer drought stress. Autumnal low flows show little difference relative to the historical period. Conversely, autumnal high flows are projected to increase.

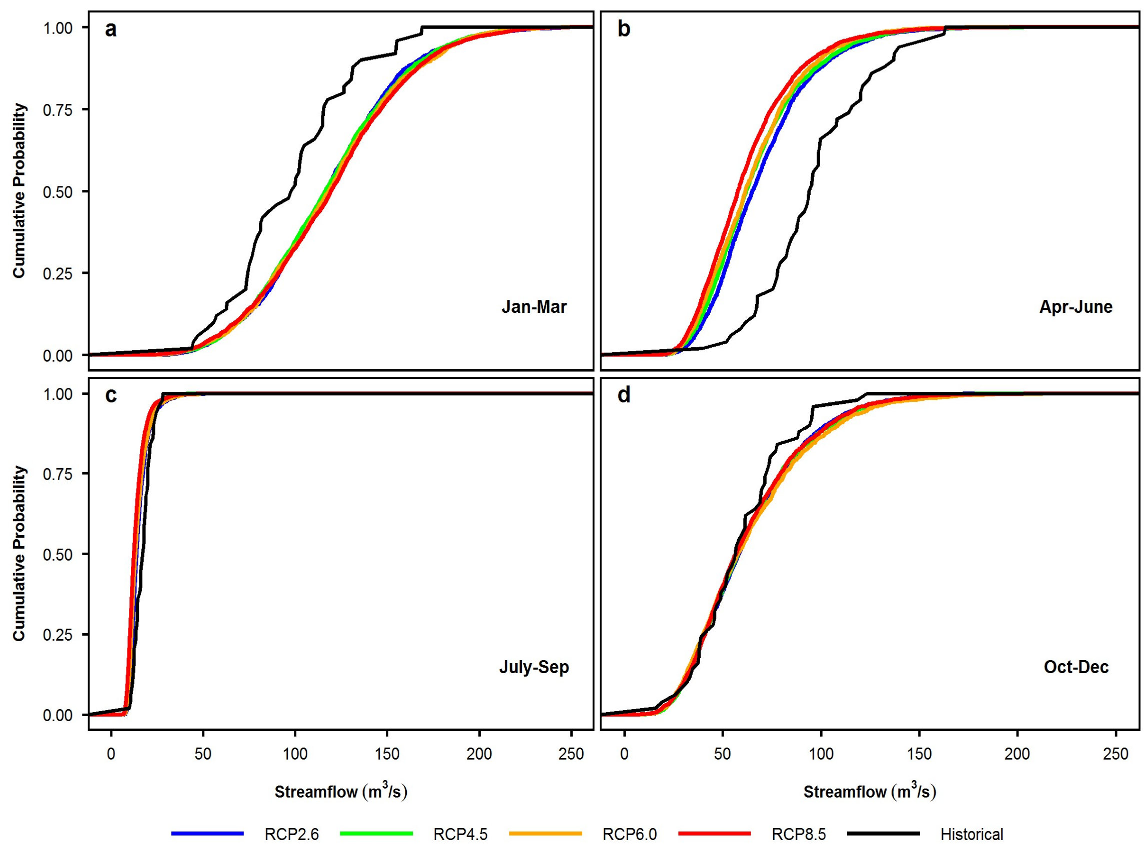

Fig 10. Seasonal cumulative probability of streamflow for each season under all RCPs for the period 2000- 2090

3.4 Sensitivity of reservoir performance to fitting period and GCM selection

Given the large variability between GCMs illustrated in the previous sections, we evaluate the sensitivity of simulated reservoir performance to the time period used for analysis and the choice of GCM. Figure 11 depicts the projected reliability using two historical and two future time periods to fit the rule curve parameters. For these results, the reliabilities are calculated by simulating the future period for each model based on a rule curve fit to the same GCM over the fitting period. Note also that only simulation periods occurring after the fitting period are evaluated, therefore for the two historical fitting periods we evaluate three future simulation periods, but for the two future fitting periods we evaluate two future simulation periods for 2000-2030 and one for 2030- 2060.

While the use of historical rule curves result in higher reliabilities during 2000- 2030 simulation period compared to periods 1950- 1980 and 1970- 1999, they do not perform well during the other two future periods. This is consistent with the trend of declining water supply during future periods shown in Figure 9. Although the reliability decreases moving further towards the end of the century, the median reliabilities of the two future simulation periods (2000– 2030 and 2030– 2060) are very similar to each other using all four fitting periods. This indicates that the reliabilities are not sensitive to the fitting period used to derive the rule curve. There is however a decrease in the range of future reliabilities when later fitting periods are used, showing a slight increase in the consistency of results when fitting periods closer to the simulation period are selected for the analysis.

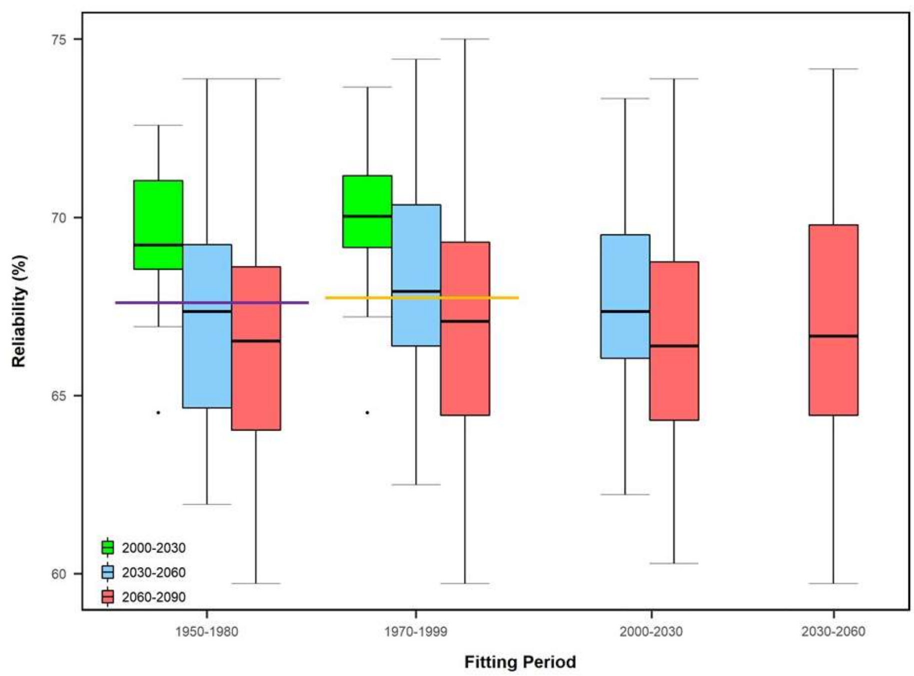

Fig 11. Historical and future simulated reservoir reliability using rule curves fit to periods 1950- 1980, 1970- 1999, 2000-2030, and 2030- 2060. Purple and orange solid lines represent simulated reservoir reliability over periods 1950- 1980 and 1970-1999, respectively

Next, we evaluate variability among GCMs behaviors by assessing whether rule curves fit with one GCM perform similarly when simulating other GCMs (i.e. comparing the reliability of rule curves fit to the same GCM that is simulated to the reliabilities when the rule curve fit to one GCM model is used to simulate the other 15 GCMs). For each model, the reservoir policy for 2000- 2030 was used to simulate the streamflow time series of that specific model and also the other 15 models over the periods 2030-2060 and 2060-2090 (Figure 12). The reliabilities of the models simulating themselves are shown on a 1:1 to illustrate if using the rule curve fit over each model results in a greater or lower reliability when simulating the other GCMs (i.e. points falling above or below the 1:1 line respectively). As shown in Figure 12, the two models with the lowest on- self reliabilities (~62%) have rule curves that perform better on every other simulation. Conversely, the models with the highest on-self reliabilities tend to do worse when simulating other models. In all cases, there is a similar range of reliability values for each GCM. This indicates that the high performing rule curves derived from the simulation do not perform systematically better or worse when applied to other GCMs.

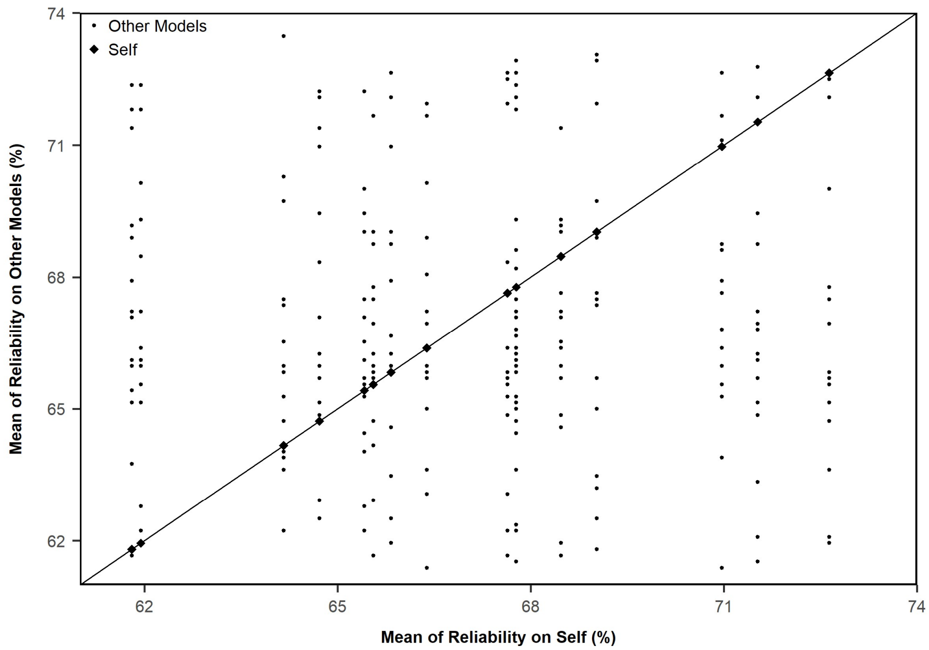

Fig 12. Mean of reliability of models simulating themselves and other models over period 2030- 2090 using policies fit over 2000- 2030 period

The analysis presented in Figure 12 is further expanded to consider performance using different fitting periods. As with Figure 12, rule curves fit to each GCM are used to simulate reservoir operations over the same GCM and for the other 15 models over the simulation period. This results in a total of 48 rule curves (16 GCMs with three fitting periods each). The policies optimized using the two historical time periods are also applied to the 16 models for the three future simulation periods for references.

Figure 13 shows the variance of reliability for each model used to simulate the other 15 models compared across three future time periods. As shown here, for each fitting period, the spread between models (i.e. the variance) increases into the future. This shows that the uncertainty of the models' predictions of the following periods compared to the period that they are fit, increases and the behavior of the models diverges. Overall, for each simulation period, simulations using the policies fit over the 2000- 2030 period result in lower variance comparing to those fit over 2030- 2060 and 2060- 2090 periods, showing that they are attributed to a larger portion of uncertainty in streamflow projections compared to 2000- 2030 period. While there is potential for greater variance when using future fitting periods, the variances of reliability across the models simulated using the historical rule curves also increase over time. For the simulation periods 2000- 2030 and 2060- 2090, the policy fit over 1950- 1980 shows a better performance comparing to the 1970- 1999 period, while the variances of the simulated values in the period 2030- 2060 using the two historical policies are almost equal.

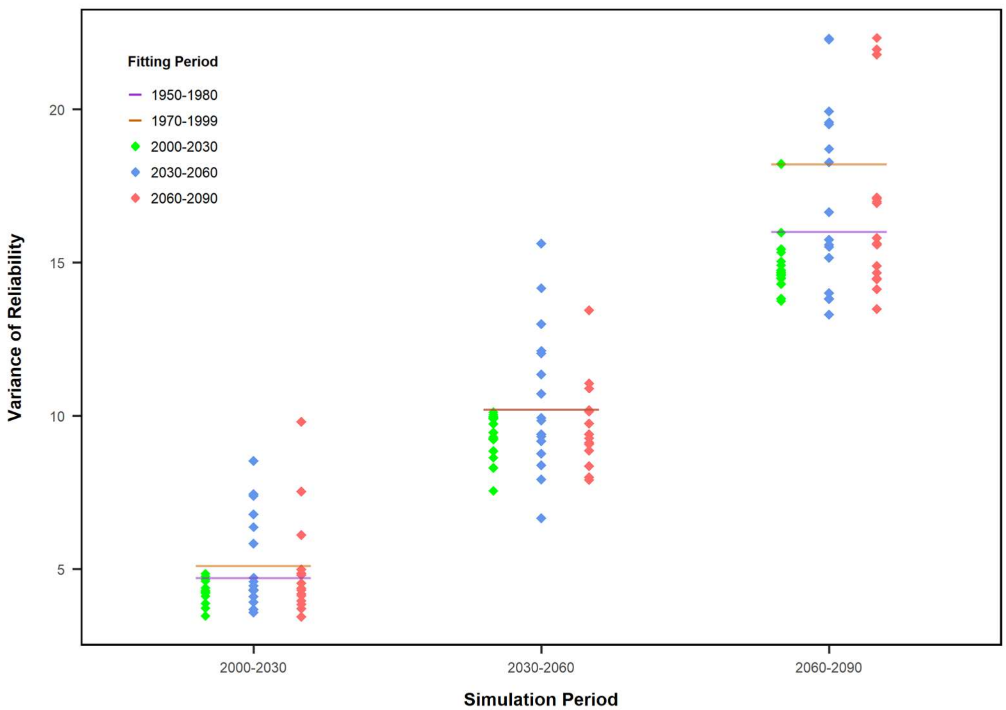

Fig 13. Variance of reliability across GCMs over future simulation periods using two historical and three future fitting periods

4. Discussion

Comparing projected reservoir releases between 16 GCMs, we found that the variability between GCMs is very great. This is expected due to the large variability in GCM simulations. The data used in this study are from four different scenarios with various level of CO_2 emissions, resulting in varying temperature and precipitation and consequently the streamflow used as the input to the reservoir. Even within each scenario, the magnitude of the differences in the release (Re) is high, indicating that the model uncertainty can play a dominant factor for this large variability. Despite variability between scenarios, there is an overall trend of decreasing reliability moving to the future. As indicated in Figure 9, using the historical rule curve (1970-1999) for operation of the reservoir results in reduction of reliability over future periods. However, 2000- 2030 period show greater projected reliability which can be due to the fact that the temperature increase is not significant during this period. The variability and reduction in reliability are in agreement with releases results which suggest an uncertainty involving in the model projections.

Results are consistent using the rule curve fit over future periods as compared to the rule curves fit to the historical time period. The use of policies fit over each model to simulate the same model in the following periods, suggests a large variability in the reliability. In fact, calculating the reliabilities by simulating the future period for each model based on a rule curve fit to the same GCM, results in a large variability. Differences among forcing scenarios are the dominant factors for this variability. When a historical rule curve is used for simulation, most models show lower reliability during 2030- 2060 and 2060- 2090 compared to the historical periods. This is likely caused by two factors; (1) the advanced timing of the streamflow peak which is consistent with field studies (e.g. Cayan et al. 2001; Regonda et al. 2005; Mote, 2006;

Nayak et al. 2010) and (2) the increased probability of low flow years and more extreme low flow events in future climate simulations. Most models predict increased streamflow during winter and a reduced spring freshet consistent with field studies (e.g. Luce and Holdon, 2009; Lundquist et al. 2009; Huntington and Billmire, 2014). Historically, the first day of April has been a transition point in water resources management. Prior to this time, the reservoirs are filling and the main purpose of the reservoir operations are to control floods. From April through July, water is released and the purpose of reservoir operations will alter to supply water generated from snowmelt runoff (Chung et al. 2009). Water supply forecasts are based on runoff forecasts for these four months. This advanced timing of peak annual streamflow decreases early spring runoff and results in a decrease in the amount of water stored in the reservoir to be used in the time of high demand.

There is no clear impact on the simulated reliability if different fitting periods are applied. This is likely due to the intrinsic uncertainty in the future simulations, which exceeds the variability among time periods. Sensitivity to model selection was analyzed by comparing the reliability on self with reliability on other. Regardless of the model selected for the policy of the reservoir, the results suggest similar range of reliabilities, implying that there is no ideal model to be considered to have the best performance in operation of the reservoir. Consequently, an ensemble of GCMs should be considered to project releases of the reservoir under future alternatives.

A particularly important point is the sensitivity of the reservoir performance to the periods which is indicated by comparing the range of variance of the reliability of all the models in different periods (Figure 13). Even though no trend is observed in streamflow time series of the models under different emission scenarios, high variances can be seen among the reliabilities moving to the future. This is related to different projections estimated by various models, as different models display a different response to the same forcing. Even a slight change in climate model temperature projections results in large differences in projected streamflow, and consequently on the reliability of the reservoir. As it can be seen in Figure 13, the projected increase in the variances is greater during 2060- 2090 period compared to earlier periods.

5. Conclusion

Analysis of the results illustrates large variability in releases across 16 GCMs during 2000-2090 period when the historical policy is used to simulate the release, ranging from 60% to 75%. The results also show that the reliability is likely to decrease into the future, which is an indicative of necessary changes required in reservoir rule curves over future periods. While 2000- 2030 period shows higher reliability, the majority of models during 2030- 2090 suggest lower reliability compared to historical periods with reliability equal to 67%. Additionally, the use of different rule curves fit over different periods illustrate no change in the reliability of the reservoir due to the great variability between GCM simulations. Our results indicate that the general trend for decreasing reliability over time is not sensitive to the time period selected or the choice of GCM. The range of on-self reliabilities varies between 62 to 74% which is similar to the range of on-other reliabilities. However, there is great variability between simulations and there are some GCMs that would indicate a hydrologic regime which could have higher reservoir reliability. The magnitude of these variabilities can be affected by the future water demand scenarios. The results mentioned above are based on the assumption that water demand is not changing moving to future. However, it is expected that water demand increase by a large factor in future caused by population growth and warmer temperature, affecting future reservoir operations (Stakhiv et al. 2016). It should also be noted that VIC includes some limitations needed to be considered (U.S. Bureau of Reclamation, 2012). VIC is assessed for monthly and annual time- scale but not daily. The scale of the grids in VIC are of coarse resolution implying that it suffers from significant biases when used for small watersheds. Also, VIC does not consider the vertical movement of moisture caused by groundwater which limits its performance in modeling surface and subsurface interaction. While VIC does have limitations, it has been widely used in many diverse environments for assessment of water resources studies (Nijssen et al. 2001; Haddeland et al. 2007; Adam et al. 2009; Ashfaq et al. 2010; Oubeidillah et al. 2014; Zhou et al. 2016) and hydrologic response of climate change in snow dominated basins (Christensen and Lettenmaier 2006; Hidalgo et al. 2009; Cherkauer and Sinha 2010). Compared to based or lumped models, VIC responds to changing temperature and precipitation in a more physically way which makes it a promising tool for climate change studies (Dwarakish and Ganasri 2015). It has been extensively applied with the outputs from GCMs for hydrologic predictions (Wang et al. 2008; Shukla et al. 2013).

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